DLDW: Deep Learning and Dynamic Weighing-based Method for Predicting COVID-19 Cases in Saudi Arabia

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Summary
Multiple waves of COVID-19 highlighted one crucial aspect of this pandemic worldwide that factors affecting the spread of COVID-19 infection are evolving based on various regional and local practices and events. The introduction of vaccines since early 2021 is expected to significantly control and reduce the cases. However, virus mutations and its new variant has challenged these expectations. Several countries, which contained the COVID-19 pandemic successfully in the first wave, failed to repeat the same in the second and third waves. This work focuses on COVID-19 pandemic control and management in Saudi Arabia. This work aims to predict new cases using deep learning using various important factors. The proposed method is called Deep Learning and Dynamic Weighing-based (DLDW) COVID-19 cases prediction method. Special consideration has been given to the evolving factors that are responsible for recent surges in the pandemic. For this purpose, two weights are assigned to data instance which are based on feature importance and dynamic weight-based time. Older data is given fewer weights and vice-versa. Feature selection identifies the factors affecting the rate of new cases evolved over the period. The DLDW method produced 80.39% prediction accuracy, 6.54%, 9.15%, and 7.19% higher than the three other classifiers, Deep learning (DL), Random Forest (RF), and Gradient Boosting Machine (GBM). Further in Saudi Arabia, our study implicitly concluded that lockdowns, vaccination, and self-aware restricted mobility of residents are effective tools in controlling and managing the COVID-19 pandemic.
Key words:
COVID-19 Prediction, Deep Learning, Random Forest, Feature Importance

1. Introduction

SARS-Cov-2 is a pathogen that changed the world, affected us physically, mentally, economically, and socially. This virus has caused 210,868,660 global confirmed cases and 4,415,304 global deaths by 20 August 2021 [1]. The second wave of the COVID-19 pandemic is far more severe both in terms of cases and deaths. Countries like the United States, Brazil, India, and Indonesia are devastated during the second wave due to the COVID-19 mutants. Some of the main reasons why some countries will soon have the third wave are: (1) the emergence of COVID-19 mutants, (2) lack of COVID-19 appropriate behaviour, and (3) vaccine hesitancy. For example, it has been predicted that the third COVID-19 wave will probably hit India in the months of September-October, and some say it can be at the start of the year 2022 [2], [3]. Despite the availability of vaccines, COVID-19 mutants are the cause of significant concerns due to the ability of mutants to escape vaccine-induced antibodies [4], [5].

In contrast, relaxing lockdown and mental fatigue encourage people not to follow COVID-19 guidelines and trigger third waves [2]. Now researchers are busy predicting the timing of the imminent third COVID-19 wave. Growing vaccine hesitancy also contributes to fewer vaccinated individuals [6]–[8]. Countries like Italy, the United States, Britain in the first wave, and the United States, Brazil, India, Indonesia in the second wave suffer more because of lack of preparation that would help them manage medical resources such as oxygen, ventilators, masks, medicines, doctors, nurses, and beds. Particularly for India and Indonesia, second-wave magnitude is so much that it surprised their overall preparations and medical infrastructure.

All the above developments point out one critical aspect: the significance of correct or near certain predictions. Today, there are various COVID-19 models to predict surges, peaks, and deaths from the infection. An efficient model will help to find answers to the questions such as (1) when the peak will come, (2) what factor contributing to the surge, and (3) implications of various COVID-19 scenarios. This issue is now even more critical in the imminent third COVID-19 wave in India and some other countries. The focus of our work is on Saudi Arabia, which has very effective COVID-19 management and control policies [9]. Figure 1 depicts that Saudi Arabia, in the second wave, maintained a high testing rate and a high daily vaccination rate, resulting in a low number of daily cases and a low death rate. This may reflect their experienced learned from MERS [10], [11]. Further, Saudi Arabia is at the forefront of successfully mass vaccinating its residents.

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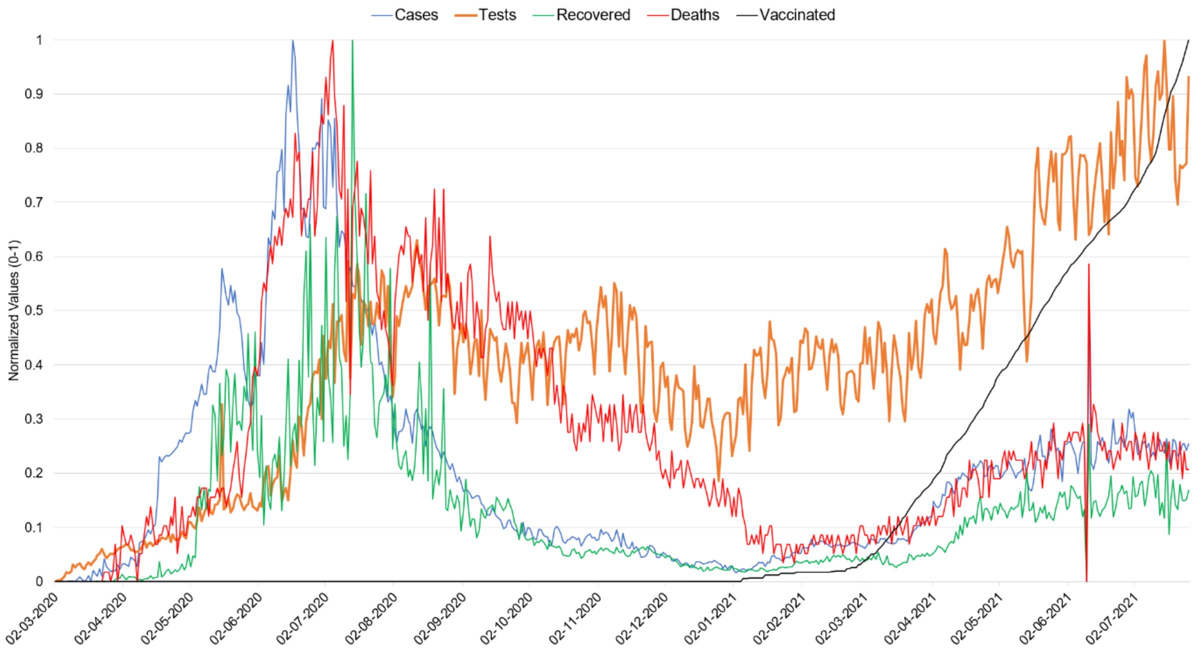

Fig 1. COVID-19 daily case, test, recovery, deaths, and at least one dose vaccinated percentage of Saudi resident population till 26-07-2021.

Concentrating on the above aspect, the contributions of this work are three-fold. Firstly, to develop a Covid-19 cases prediction method focused on pandemic measures and residents' mobility. Secondly, to develop a Covid-19 cases prediction method that is dynamic to accommodate evolving factors affecting the pandemic. Thirdly, to develop a Covid-19 cases prediction method that is simple to model and scalable. COVID-19 devastated the world from 2020. Initial prediction models have limited factors affecting them. However, as pandemics evolve, new factors start playing an important role, such as mutants, vaccines' introduction, fatigue from lockdowns, and COVID-19 appropriate behaviour. Due to this fact, previous COVID-19 models are not useful as they face serious scalability issues. The proposed method is scalable as it is designed keeping in view the addition of new factors.

To the best of our knowledge, no previous work exists which addresses the points mentioned above. With the help of advanced methods, we can prepare and allocate various critical resources necessary for COVID-19 controlling and management to avoid chaos during infection peaks in society. The paper is divided into five sections. The next section contains a literature review of the related research. In Section 3, we explain the proposed method in detail. In Section 4, we discuss the results, and in Section 5, we conclude the paper.

2. Literature Review

COVID-19 infections and peaks prediction models have become a critical part of COVID-19 policymaking and public debate. These models guide government, healthcare experts, businesses, and COVID-19 logistic vendors to get prepared to face pandemic challenges to maintain prosperity in society. The majority of these models fall short of the accuracy that has been desired from them, which is the cause of irritation among policymakers and scientists because resource allocation, emergency measure preparation, funds, human resources largely depend on these prediction models. For example, the Susceptible, Undetected, Tested (positive), and Removed Approach (SUTRA) Indian model predicted a peak of 100 thousand cases a day during the second COVID-19 wave, which was disastrously incorrect. India saw 400 thousand cases a day during the peak of the second COVID_19 wave. SUTRA and today's COVID-19 forecasting model depend on too many parameters, which resulted in their debacle because mapping many parameters near certainty is a challenge in itself [12]. Slow vaccination pace, mainly highly infected Delta and Delta+ COVID-19 mutants destroyed these models, which these models never considered a critical factor until it's too late.

However, despite low credibility, every model highlights essential information about the pattern of how the COVID-19 pandemic can increase or decrease and related factors. COVID-19 prediction models are more local rather than global. For example, Tuite et al. [13] proposed a mathematical model to predict new infection cases in Ontario, Canada. The finding suggested that physical distancing and tracing new cases play a vital role in managing and controlling the pandemic. Otherwise, healthcare resources, and particularly ICUs, can be overwhelmed. Another area-specific work [11] proposed a statistical model for mainland China to predict pandemic characteristics that contribute to new cases, deaths, and recoveries.

After vaccination begins, COVID-19 prediction models need to consider vaccination rate as a parameter that may positively reduce infection. The effect of vaccination is different from humans to humans. However, if we see in generalization, vaccinations tend to protect people against COVID-19 different variants. In such a work, Usherwood et al. [14] proposed a model which considers two vital and dynamic population behaviors. Firstly authors take into account caution level and, secondly, safety parameters. In [14], the authors predicted COVID-19 trends based on vaccine availability and behavior. The model predicted that in August 2021, there would be zero cases as per the current vaccination rate; this may seem to be a near prediction if vaccines can provide immunity against mutant viruses. Today, with the presence of the internet, we do not just have medical datasets, but social datasets also help us find patterns from hidden social behaviors of internet users. Yousefinaghani et al. [13] moved beyond traditional datasets and developed a prediction model that uses social media data to perceive how COVID-19 will evolve in Canada and U.S.A. With tweets data, the model can produce 100% accurately for first waves 78% correctly for second waves. This shows that social media data holds essential insights into the health of individuals. The Liu et al. [14] prediction model focused on different reopening strategies in different areas of U.S.A and their effect on of new cases.

Fusion of sophisticated technologies like the Internet of Things [15],[16], Edge and Fog computing [17]–[20], and Artificial intelligence (AI) [21], [22] are at the forefront of promisingly predicting various aspects of the COVID-19 pandemic [23]–[25]. One such effort by Alam et al. [26] focused on developing an intelligent Covid -19 response system. This paper proposes a technology-driven framework, iResponse, a fusion of artificial intelligence, sensors, and connectivity technologies. Allow monitoring the pandemic-related queries, resource planner. In iResponse framework, all modules work simultaneously and give useful information. According to Google's data, the five most affected countries are India, U.K., Brazil, and U.S., Mexico. iResponse consists of a dynamic prediction model for COVID-19, which uses a universe of data sources such as tests results, social media, mutants, resources, etc. Appadu et al. [27] and Nabi et al. [28] did a critical comparative analysis of various COVID-19 prediction methods based on statistics and artificial intelligence. Cubic spline interpolation, Euler's iterative method, and variants are compared in [19] on South Korea, South Africa, India, Italy, and Germany datasets. Four deep learning models are used in [28], which are convolutional neural network (CNN), gated recurrent unit (GRU), long short term memory (LSTM), and multivariate CNN (MCNN) for Brazil, Russia, and UK environments. Results showed that CNN outperformed the others.

The countries that successfully controlled COVID-19 during the first wave are now struggling with new surges in the cases [29]. Particularly South-East Asia is witnessing new surges in cases, and the medical healthcare system is under breakdowns, such as Bangladesh, Indonesia, Thailand, and Myanmar. Further recent lockdowns in China and Australia are also a cause of concern due to increasing cases of Delta-variant. In the wake of all these events, the role of COVID-19 prediction models is very critical as it will help the country's establishment to get ready and prepare the needed resources to avoid chaos during the future COVID-19 peaks. In this work, we proposed a COVID-19 prediction method that can better accommodate the evolving pandemic factors such as new variants, vaccination rate, information campaign, etc.

3. Methodology

COVID-19 infection prediction is a topic of significant importance from the research community and its implications on society. In this work, we proposed a COVID-19 daily new infection prediction method based on deep learning and dynamic weighing. The primary issue with any pandemic prediction method is that it becomes increasingly difficult and complex to model as several features increase with time, affecting the pandemic [30]–[36]. This results in poor modelling assumptions with scalability issues, which finally leads to poor decision making and policy formulation. We named the proposed method as Deep Learning and Dynamic Weighing-based (DLDW) COVID-19 daily cases prediction method for Saudi Arabia. In this work, we rely on factors affecting the pandemic, and resident mobility to predict daily COVID-19 cases in Saudi Arabia. Figure 2 depicts the steps of the DLDW method. Firstly, we merged the World Bank dataset [29] and the Google mobility dataset [37]. Secondly, we have given two dynamic weights which change periodically. First, increasing weight is assigned to features that hold the maximum importance, and the second weight is assigned to data instances (rows) based on how old they are. For example, more weight is assigned to COVID-19 data for 2021, and less importance is assigned to data for 2020. It is an interactive process, which periodically updates the weights. We added two new weight features as explained above to the dataset. Thirdly, we performed a deep grid search to find out a best possible model for the given training data. In DLDW, it is easy to add or remove new features without changing much of the method. Thus, DLDW is scalable in terms of evolving features.

3.1 Data Preparation

This section provides details of the dataset used in this work. Figure 2 depicts the various features that we have used in this work. In this work, we used two datasets. The first one is the World Bank COVID-19 dataset [38]. It consists of over fifty variables. These variables could be used for COVID-19 related studies. From these variables, we used 12 variables that are related to pandemic measures. We call them pandemic measures henceforth. The dataset contains the daily pandemic measures and the number of COVID-19 cases (the 13th variable) for almost all countries worldwide. The titles of these pandemic measures are listed in Figure 3, along with the various options defined for these pandemic measures. For example, the first pandemic measure listed on the top left of the figure is “School Closures”. The various options for this pandemic measure are to take no measures, recommend closing the school (but do not enforce), enforce closing the schools but for some levels, and enforce closing schools for all levels. The second dataset is the Google COVID-19 mobility report dataset [37]. This dataset consists of six mobility features recorded during COVID-19: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas. Figure 3 depicts the range of cases labelled in classes (R1, R2, R3… R10).

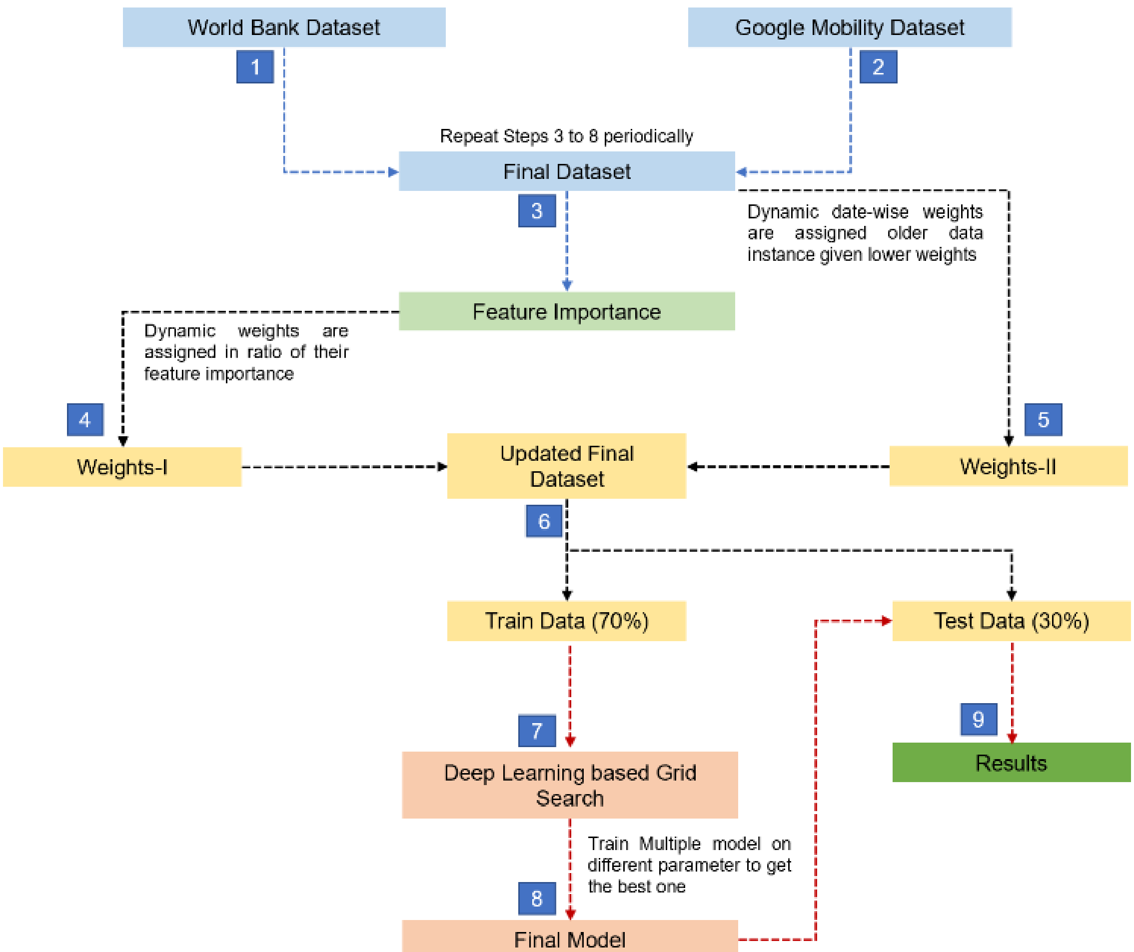

Fig 2. Deep Learning and Dynamic Weighing-based (DLDW) COVID-19 cases prediction method.

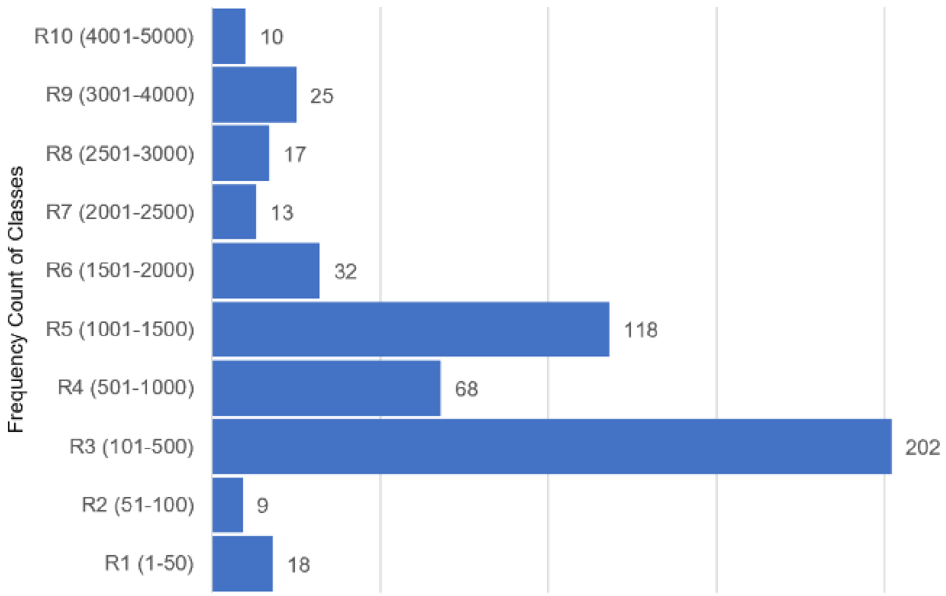

Fig 3. Frequency count of the classes.

Details of Pandemic Measures

Workplace Closures (PM11)	
0	No measure
1	Closure recommended
2	Require to close (some sections)
3	Require to close (all sections)

School Closure (PM07)	
0	No measure
1	Closure recommended
2	Require to close (some sections)
3	Require to close (all sections)

Public Transport Closure (PM02)	
0	No measure
1	Closure recommended (reduce volume)
2	Closure needed

Internal Movement Restrictions (PM06)	
0	No measure
1	Movement restrictions recommended
2	Total movement restrictions

Stay at Home (PM08)	
0	No measure
1	To be in house recommended
2	To be in house (some expections)
3	To be in house (no expections)

Testing Policy (PM10)	
0	No testing policy
1	Test (with symptoms & on specific creteria)
2	Test (based on symptoms)
3	Testing open to all

Cancel Public Events (PM01)	
0	No measure
1	Cancelation recommended
2	Cancellation needed

Public Information Campaign (PM04)	
0	No information campaign
1	Requests & warning by administration
2	Well Coordinated campaing

International Travel Restrictions (PM03)	
0	No restrictions
1	Screening needed
2	Quarantine (from high-risk regions)
3	Ban on high-risk regions
4	Total travel ban

Gathering Resttictions (PM05)	
0	No restrictions
1	Restrictions (up to 1000 people)
2	Restrictions (100-1000 people)
3	Restrictions (10- 100 people)
4	Restrictions (up to 10 people)

Contact Tracing (PM12)	
0	No Policy
1	Limited contact tracing
2	Comprehensive contct tracing

Stringency Index (PM09)
This is the composite, Nine pandemic measures are used in it. Computed on scale (0 to 100). 100 means strictest

Mobility Features

MF01	Grocery & Pharmacy
MF02	Parks
MF03	Resdential
MF04	Retail & Recreation
MF05	Transit Stations
MF06	Workplaces

Fig 4. Details scale of measurement for various pandemic features and mobility features codes.

3.2 Feature Importance

The feature importance signifies the features that are contributing the most to the response variable. This means how much a pandemic measure and mobility feature helping in the prediction of the response variable (range of cases). Finding feature importance is critical from the perspective of a long-going pandemic with multiple waves like COVID-19. Various factors affecting the pandemic are evolving during the time. We used the Boruta algorithm for performing feature selection [39]. It is a wrapper around the RF algorithm. It iteratively selects and removes irrelevant features using statistical techniques. Figure 5 depicts the importance of various features in our datasets. For feature importance, we aimed to see that does the factors affecting the pandemic are changing and by how much. For this purpose, we divided our dataset into two parts based on years (2020, 2021). It is evident through Figure 4 that there is a considerable change in feature importance of the COVID-19 pandemic in Saudi Arabia from 2020 to 2021. For example, the Stringency index feature was having the importance of 20 during the year 2020 whereas, in the year 2021, it is only just above 6. In contrast, vaccine importance is highest in 2021, which means that introduction of vaccines is affecting a number of cases, as depicted in Figure 5.

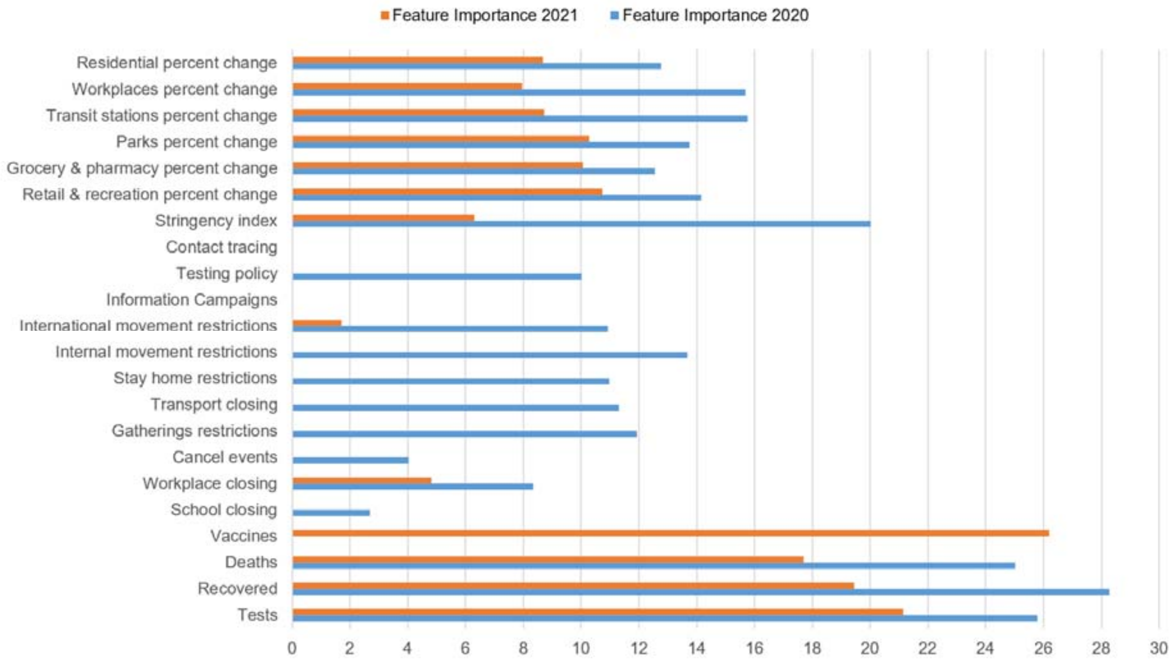

Fig 5. Feature importance of various factors related to COVID-19 pandemic.

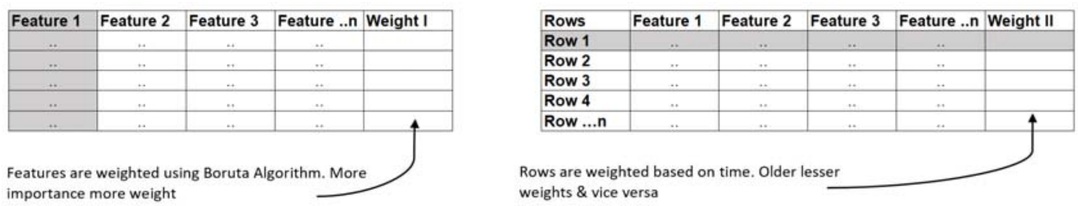

Fig 6. Features and rows are weighing.

3.3 Dynamic Weighing

All the features are normalized. We assigned two types of weights, as depicted in Figure 6. The first is vertical weight, assigned to features, higher weights to features with higher importance, and vice-versa. The second one is horizontal weight, which is added based on older data instances with lower weights than the dataset is updated and divided into 0.70 and 0.30 ratios for training and testing.

3.4 Deep Learning

Feed Forward Deep Neural Networks, also known as a multi-layered perceptron for DL [40], are used for prediction purposes. They consist of an input layer (data), hidden layers (neurons), and an output layer. We performed a grid search to know the best possible and most efficient DL parameter, producing the best results [41]. DL grid search is implemented using the H2O deep learning library in R [42]. We trained 128 DL models as depicted in Figure 7 and based on the best model we selected DL model with 80 epochs, hidden c(128,128), balance classes = true, activation = "Tanh", l1 = 0.0001, l2 = 0.0001, adaptive rate = TRUE, rho = 0.99, rate = 0.005, and rate annealing = 1e-06.

4. Results and Analysis

To evaluate the performance of the DLDW method, confusion matrix is used as a performance measuring benchmark. With the help of confusion matrix we can calculate the prediction accuracy percentage, sensitivity, and specificity [43]. To demonstrate the validity of the

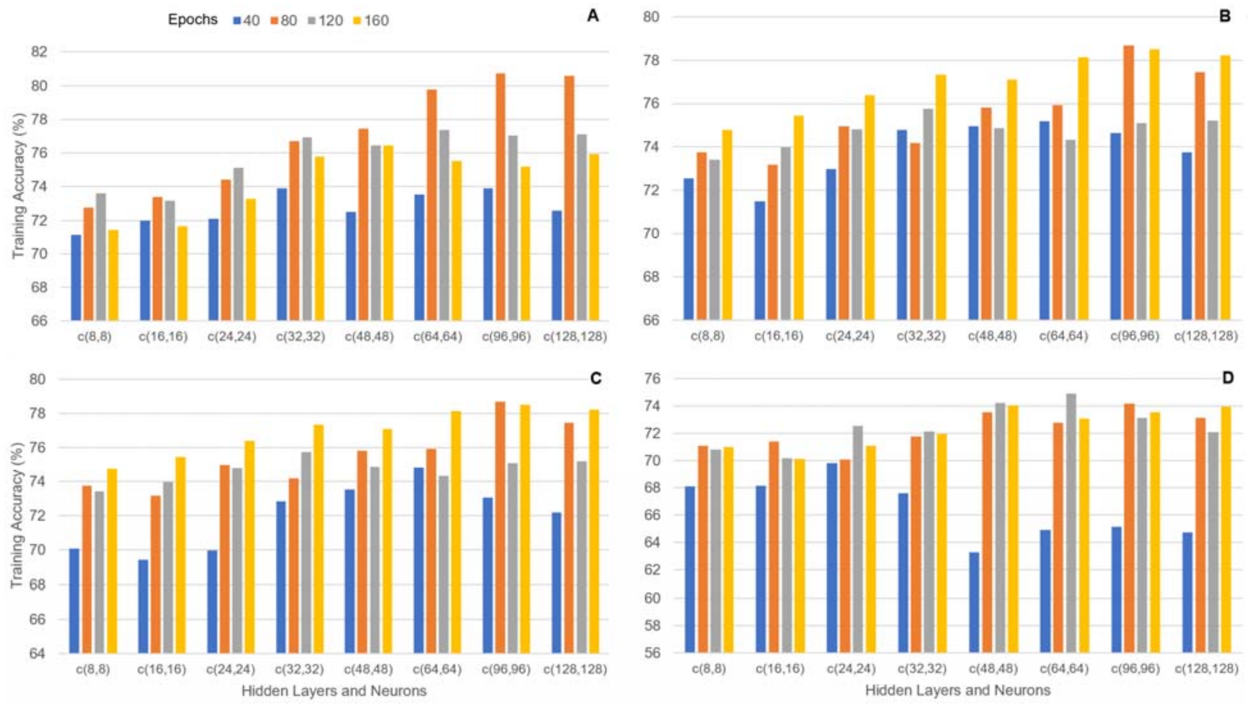

Fig 7. Grid search results of 128 deep learning models in Prediction accuracy (%).

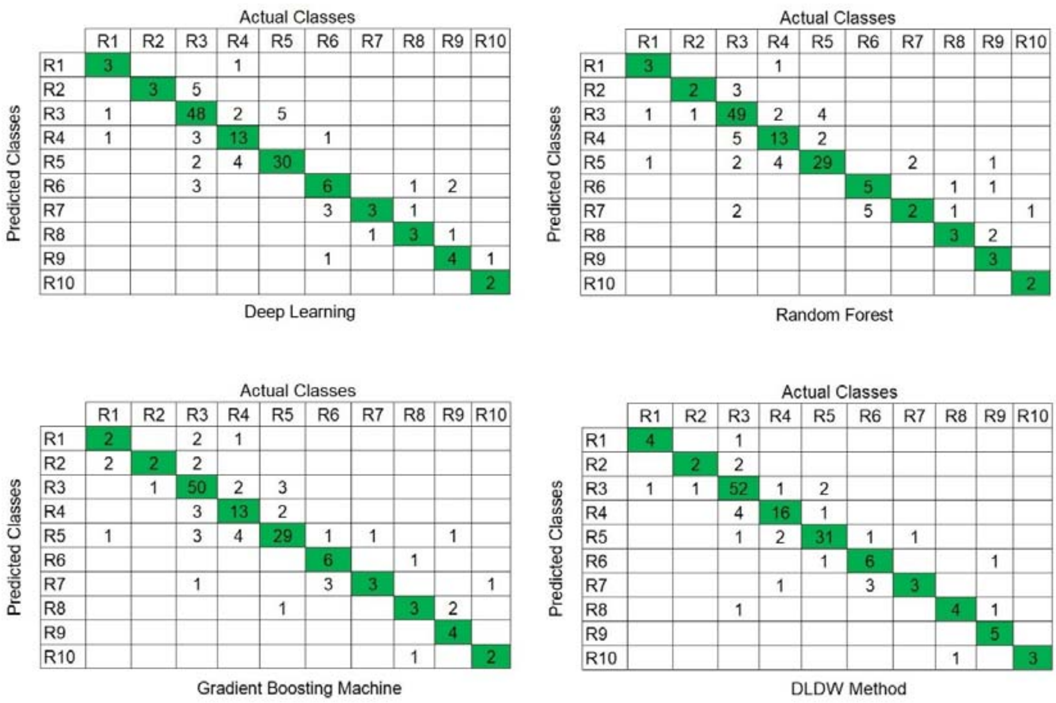

Fig 8. Confusion matrix of DL, RF, GLB, and DLDW.

performance of the DLDW method, we compared the results of DLDW from three state-of-the-art classifiers which are: DL, RF, and GBM. RF is uses ensemble learning technique called bagging, and capable for classification and regression tasks. RF is a highly capable classifier that can handle high-dimensionality, and can also compute feature importance in a dataset. It also helps to avoid overfitting [44]. Whereas GBM [45] uses ensemble

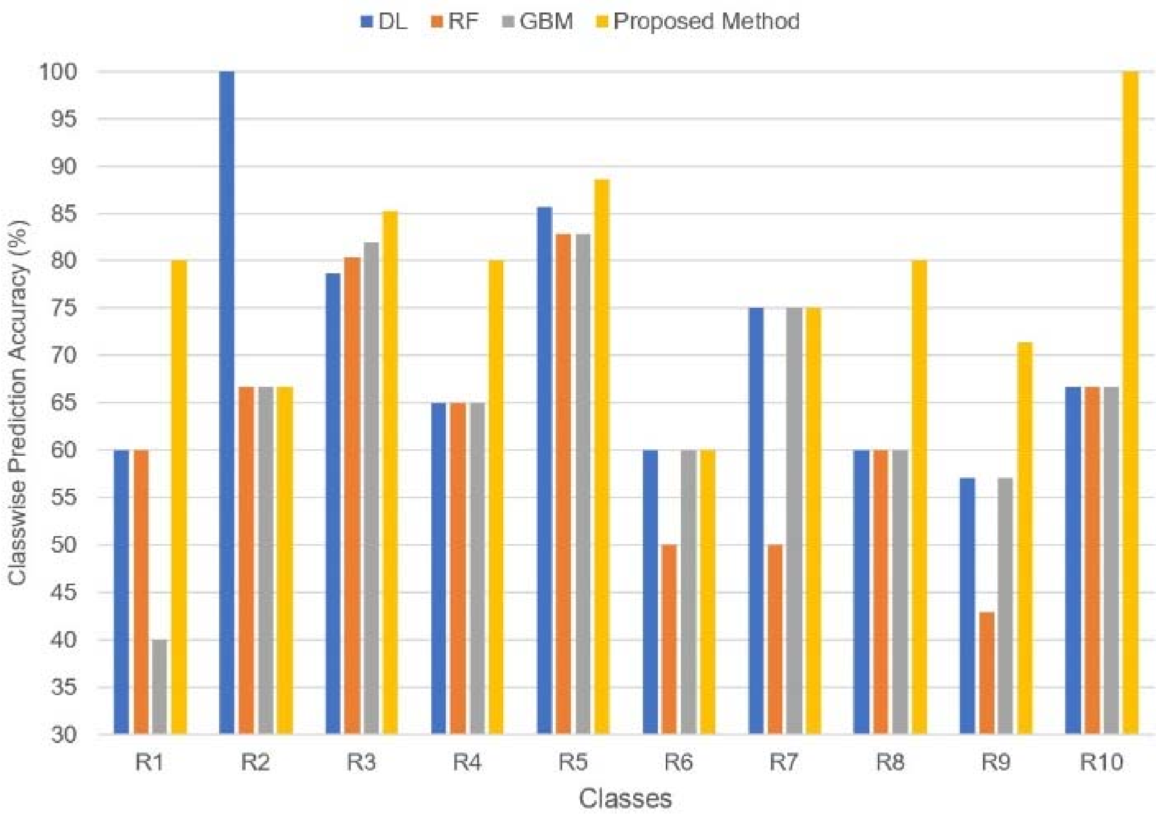

Fig 9. Class-wise prediction accuracy (%).

learning technique called boosting that combines weak learners to form a strong classifier.

4.1 Prediction Accuracy

Figure 8 depicts the confusion matrix of DL, RF, GBM, and DLDW method. We have seen the DLDW method outperformed all others. The DLDW method produced 80.39% prediction accuracy, whereas DL, RF, and GBM produced 73.85%, 71.24%, and 73.20% prediction accuracy, which is 6.54%, 9.15%, and 7.19% lesser than the DLDW method. Figure 9 depicts class-wise accuracy percentages. The DLDW method produced better class-wise accuracies for seven classes out of ten. Only in the case of R2 class, DL produced better accuracy than the DLDW method. Figure 8 and Figure 9 show that the DLDW method outperformed the other three schemes: DL, RF, and GBM.

4.2 Correlation Matrix

Figure 10 depicts the correlation matrix of daily new cases, vaccinated population percentage, pandemic measures, and mobility features for Saudi Arabia till 13th August 2021. We computed the correlation matrices of the six mobility features with twelve pandemic measures using the cor() function of the stats package [46] in R.

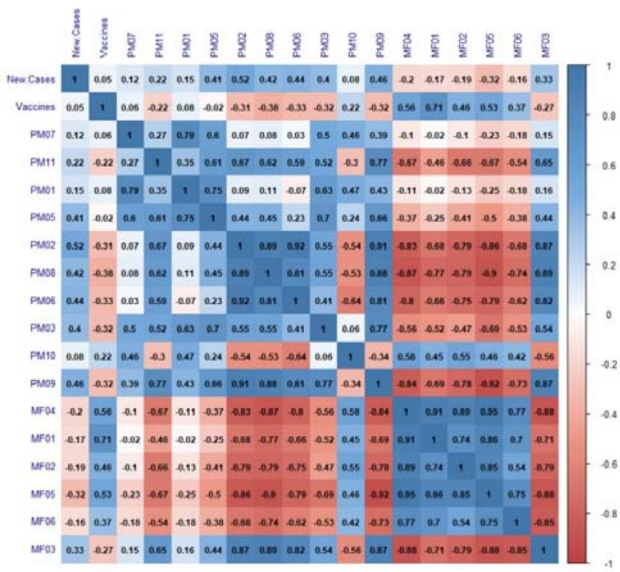

Fig 7. Correlation matrix of Saudi Arabia from 2020 to 2021

There is a robust correlation between the mobility features and some pandemic measures. For example, MF04 has a very strong negative correlation of -0.83, -0.80, -0.87, and 0.84 with PM02, PM06, PM08, and PM09. When retail and recreation activities increase in Saudi Arabia, public transport restrictions, internal movement restrictions, stay at home restrictions, and stringency index is at minimum levels. Further, this also signifies that COVID-19 restrictions resulted in minimizing residents' mobility. Additionally, Figure 10 shows a weak and moderate negative correlation between mobility features (MF01, MF02, MF04, MF05, MF06) and daily new cases of -0.17, -0.19, -0.32, -0.20, and -0.16, respectively. This means residents restricted their mobility as daily new cases increases in Saudi Arabia.

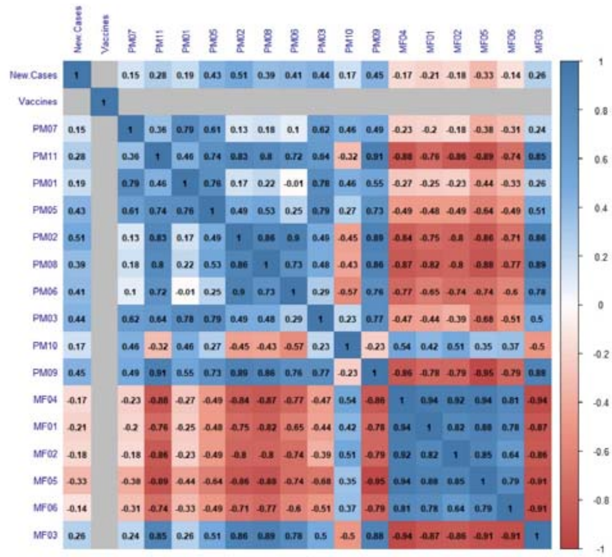

Fig 8. Correlation matrix of Saudi Arabia for the year 2020.

Figure 11 depicts correlation matrices between the same features used in Figure 10, with one difference in Figure 11; only the data until 2020 is considered. The "Grey" color row and column denoted constant features, thus there is no correlation coefficient computed for them. In the case of Figure 11, Vaccines and PM07 were constant. For example, MF04 has a very strong negative correlation of -0.84, -0.87, -0.86, and 0.88 with PM02, PM07, PM09, and PM11. When retail and recreation activities increase in Saudi Arabia, public transport restrictions, internal movement restrictions, stay at home restrictions, and stringency index are at minimum levels. Further this also signifies that COVID-19 restrictions resulted in minimizing residents' mobility. Further, Figure 11 shows a weak and moderate negative correlation between mobility features (MF01, MF02, MF04, MF05, MF06) and daily new cases of -0.21, -0.18, -0.17, -0.33, and -0.16, respectively. This means residents restricted their mobility as daily new cases increases in Saudi Arabia.

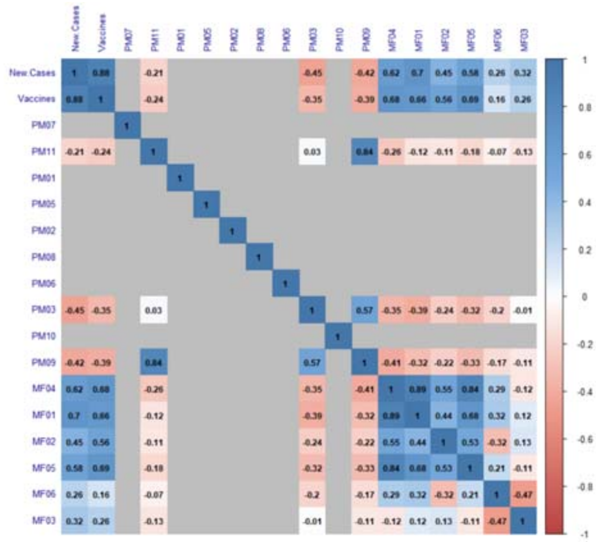

Fig 9. Correlation matrix of Saudi Arabia for the year 2021.

Figure 12 depicts the correlation matrix of the data after 31st December 2020. The "Grey" color rows and columns denoted constant features. Thus there is no correlation coefficient computed for them. In the case of Figure 12, Vaccines, and PM01, PM02, PM05, PM06, PM07, PM08, and PM10 are constant. One major difference in 2021 from 2020 is that in 2021 vaccines are introduced. However, highly infectious new COVID-19 mutants also emerge. Vaccines has correlation of 0.66, 0.56, 0.26, 0.68, and 0.69 with MF01, MF02, MF03, MF04, and MF05. Further, Vaccines have a weak negative correlation of -0.35 and -0.39 with international travel restrictions, and stringency index. Figure 5 depicts that with the increased percentage of Saudi residents vaccinated, there is an increase in mobility of the residents. Implicitly we can say that introduction of vaccines brought confidence in the administration to have milder restrictions and people are also more confident to move around after vaccination.

5. Conclusion

The world is witnessing multiple waves of the COVID-19 pandemic, and later waves are far deadlier than the previous ones. The importance of COVID-19 forecasting methods gained prominence as they help governments worldwide prepare healthcare resources well in advance. One major issue with forecasting methods is the increasing uncertainty of their prediction due to increasing factor affecting the pandemic. This is due to evolving and increasing the number of factors that are affecting the pandemic. This work addresses these issues, and special consideration has been given to the evolving factors that are responsible for recent surges in the pandemic. For this purpose, two weights are assigned to data instance (1) based on feature importance and (2) dynamic weight-based on time. Older data is given fewer weights and vice-versa. Feature selection showed which factor affecting the rate of new cases evolved over the period. The DLDW method produced 80.39% prediction accuracy, 6.54%, 9.15%, and 7.19% higher than the other three state-of-the-art classifiers. Further in Saudi Arabia, our study implicitly concluded that lockdowns, vaccination, and self-aware restricted mobility of residents are effective tools in controlling and managing the COVID-19 pandemic. In the future, we want to extend the DLDW method to form a global COVID-19 cases prediction model.

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